Omni Script Writer Identification problem

A dissertation submitted in partial fulfilment of the requirement for the Master of Technology in Computer Science degree of the Indian Statistical Institute

By

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CERTIFICATE OF APPROVAL

This is to certify that the thesis entitled ***"Omni Script Writer Identification Problem"*** is an authentic record of the dissertation carried out by **Mohammed Tarique** at Indian Statistical Institute Kolkata, under my supervision and guidance. The work fulfils the requirement for the award of the M-tech degree in Computer Science.

Dated:

....

(Dr Utpal Garain)

Supervisor

....

Countersigned

External Examiner

Acknowledgement

It has been a great honour and rewarding experience to work under the auspices of a guide as Dr Utpal garain CVPRU, endowed with amazing capability of making complex mathematical expression and impossible to understand theories seem as simple and interesting as. It has been Dr Garain’s effort and encouragement that has borne fruits in the successful completion of this project. No amount of thanks can repay his contribution to this work.

I am fortunate enough to be associated with an institute of international repute that has provided me an excellent infrastructure and environment in helping me to complete my project.

Mohammed Tarique

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Contents

Chapter 1

Introduction

OMNI script writer identification problem is basically a writer identification problem in which images of hand writing of different authors are there in our database, at this point we are given a sample image of an unknown writer and we have to tell who is the writer of this image sample.

Normally in this kind of problem our database consists of single script writing for example Hindi, English, Bengali etc. And unknown sample also comes under the same script but in case of OMNI script writer identification problem we release this restriction and allow multi-script to be there in our database.

Though it seems to be a generalization of single script writer identification problem to multi-script environment but this is not really the case and you yourself will start believing this as we will go on farther and farther into the detail of our discussion.

As far as single script writer identification problem is concerned several excellent works have already been done for script like English, Bengali, Hindi, French etc.

For most of the solution, they have used a common way of attacking this problem which is to use pattern recognition problem i.e. extraction of a set of features from the hand writing of known writer and then based on these features classify the writer of an unknown sample as one of the known writer.

They have mainly concentrated on allograph level features on a script under consideration which have been extracted by segmenting the text into lines, words, characters, graphemes etc.

The use of allograph level feature requires knowledge in a particular script i.e. how to segment word into character or graphemes etc. And therefore extension of the method based on allograph level features is not straight forward to tackle multi-script problem where writer may write in different scripts.

So we need a completely different treatment to solve our problem and need to extract those kind of features which are script independent that's why we need to go through the very low level at the pixel level of the image sample.

Previous Work

Unlike single script writer identification problem not much work have been done in this area so far. An extremely good work for solving this problem was done by my supervisor itself Dr. Utpal Garain and Mr. Thierry Paquet.

The Basic idea which these two persons have used is that they have viewed hand writing image as a sequence of pixel value and they have tried to predict value of a pixel location by using previous say n terms.

Let for the k^{th} location we want to predict its pixel value say y_k by using previous n terms. Let y_k can be written as

$$Y_k = a_1y_{k-1}+a_2y_{k-2}+..............+a_ny_{k-n}+€_n$$

Let these a_i's, i=1,2,.....,n are such that they are best to predict pixel value of all location then this coefficient vector $(a_1,a_2,......,a_n)$ are said to be AR coefficient of this image or image signal.

AR coefficient for each image represents that particular writer. Now for the unknown sample it's AR coefficients are calculated and it's Euclidian distance with AR coefficients of all other images are calculated and whichever is find to be minimum is declared to be writer of that sample. The detail of the discussion is in chapter 2

Extension towards the work

Clearly the more and more number of terms we take in order to predict a pixel value the more accuracy we will get but at the same time it would increase our computational complexity to a greater extent so there is a trade-off between size of the neighbour set and accuracy we want to achieve. The question arises at this point, *Does there exist an optimal choice of neighbour for solving this problem*

More over if we choose our nbd-set in a square or rectangle e.g. 4x4, 3x5, 5x3, this enhance our difficulty to some more extent because while implementing we see that not only size but shape also affects our calculated result for example 3x5, 5x3 both nbr set has 14 pixel value for predicting a particular location but both gives different-different results while using.

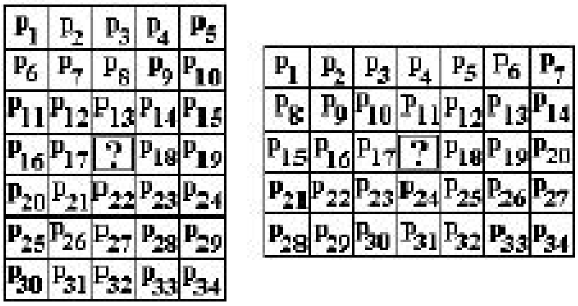
So at this point not only size but shape also is a parameter which we need to take care of. This boils down my problem of Omni script writer identification problem to suitable choice of nbr of any digital signal context .

That means for a digital signal, may be of sound, image ,speech what should a suitable choice of nbr in order to predict a particular signal value .

Below are the examples of 5x5 , 7x5, and 5x7 nbd set respectively.

P_1	P_2	P_3	P_4	P_5
P_6	P_7	P_8	P_9	P_{10}
P_{11}	P_{12}	?	P_{13}	P_{14}
P_{15}	P_{16}	P_{17}	P_{18}	P_{19}
P_{20}	P_{21}	P_{22}	P_{23}	P_{24}

(a)



(b) (c)

Different contexts used in estimating AR coefficients: (a) C1: 5x5 context (b) C2: 7x5 context and (c) C3: 5x7 context.

Chapter 2

Off-Line Multi-Script Writer Identification

2.1 AR coefficient

The definition that will be used here is as follows where

$$x_t = \sum_{i=1}^{N} a_i \, x_{t-i} + \varepsilon_t$$

Where a_i are the auto regression coefficients, x_t is the series under investigation, and N is the order (length) of the filter which is generally very much less than the length of the series. The noise term or residue, epsilon in the above, is almost always assumed to be Gaussian white noise.

Verbally, the current term of the series can be estimated by a linear weighted sum of previous terms in the series. The weights are the auto regression coefficients.

The problem in AR analysis is to derive the "best" values for a_i given a series x_t.

Solutions :

A number of techniques exist for computing AR coefficients. The main two categories are least squares and Burg method. Within each of these there are a few variants, the most common least squares method is based upon the Yule-Walker equations. Mat Lab has a wide range of supported techniques, note that when comparing algorithms from different sources there are two common variations, first is whether or not the mean is removed from the series, the second is the sign of the coefficients returned (this depends on the definition and is fixed by simply inverting the sign of all the coefficients).

The most common method for deriving the coefficients involves multiplying the definition above by x_{t-d}, taking the expectation values and normalising (see Box and Jenkins, 1976) gives a set of linear equations called the Yule-Walker equations that can be written in matrix form as

$$
\begin{pmatrix}
1 & r_1 & r_2 & r_3 & r_4 & \cdots & r_{N-1} \\
r_1 & 1 & r_1 & r_2 & r_3 & \cdots & r_{N-2} \\
r_2 & r_1 & 1 & r_1 & r_2 & \cdots & r_{N-3} \\
\vdots & \vdots & \vdots & \vdots & \vdots & & \vdots \\
r_{N-1} & r_{N-2} & r_{N-3} & r_{N-4} & r_{N-5} & \cdots & 1
\end{pmatrix}
\begin{pmatrix}
a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_N
\end{pmatrix}
=
\begin{pmatrix}
r_1 \\ r_2 \\ r_3 \\ \\ r_N
\end{pmatrix}
$$

where rd is the autocorrelation coefficient at delay d. Note: the diagonal is $r_0 = 1$.

2.2 Abstract

The problem of writer identification in a multi-script environment is attempted using a two dimensional (2D) autoregressive (AR) modelling technique. Each writer is represented by a set of 2D AR model coefficients. A method to estimate AR model coefficients is proposed. This method is applied to an image of text written by a specific writer so that AR coefficients are obtained to characterize the writer. For a given sample, AR coefficients are computed and its L2 distance with each of the stored (writer) prototypes identifies the writer for the sample. The method has been tested on datasets of two different scripts, namely RIMES containing 382 French writers and ISI consisting of samples from 40 Bengali writers

2.3 Two-dimensional autoregressive model

A discrete image defined on an $M \cdot N$ (say, $P = M \cdot N$) rectangular grid is denoted by $\{x_{ij}\}$ (i = 1, 2, …, M; j = 1, 2, …, N). When each element x_{ij} is a random variable, $\{x\}$ is called a discrete random field. In this paper, we deal with a class of random linear equation.

$$x_{ij} = \sum_{(p,q \in D)} \theta_{pq} x_{i-p,j-q} \qquad (1)$$

where D denotes the context region. Normally (but not necessarily) D is represented by a rectangular region as $D = \{(p, q) \mid -m \leq p \leq m, -n \leq q \leq n, (p, q) \neq (0,0)\}$ (2)

θ_{pq} is the AR model coefficients and pxq is the order of the model. So value of each pixel (say, $y = x_{ij}$) is predicted as a linear combination of D neighboring pixels. So in general we can write

$$y = h\,\theta \qquad (3)$$

where, y is P x1 dimensional, h is a Px D dimensional matrix and θ is D x1 dimensional. So y records value of each of the P pixels in the image. For each of these P pixels, values of the D neighboring pixels are recorded in each row of h.

2.4 Estimation of AR coefficients

Next, our problem is to estimate θ. We present this estimation by following a bra-ket notation1. Let e denote the error in predicting the value of pixel, y. So we can write

$$e = y - h\theta \qquad (4)$$

the squared error is defined as

$$J = \{e^2\} \qquad (5)$$

So

$$\begin{aligned} J &= < y - h\theta \,|\, y - h\theta > \\ &= < y \,|\, y > - < y \,|\, h\theta > - < \theta h^T \,|\, y > + < \theta (h^T h) \theta > \\ dJ &= -2 < yh \,|\, d\theta > +2 < \theta \,|\, h^T h \,|\, d\theta > \end{aligned}$$

To mininmize J dJ is set to zero i.e

$$\begin{aligned} < yh \,| \quad &= < \hat{\theta} \,|\, h^T h \,| \\ \Rightarrow \quad (h^T h) \,|\, \hat{\theta} > &= h^T \,|\, y > \qquad (6) \\ \Rightarrow \quad |\, \hat{\theta} > &= (h^T h)^{-1} h^T y > \end{aligned}$$

So estimation of theta requires matrix multiplications, transpose and inversion operations. This solution is simply the least mean square solution of equation (3).

If the AR model is applied to each pixel of an image, implementation may require large computation even for a reasonable sized image. Therefore, instead of computing AR model in all pixels in binary images, we compute the model only in black pixels. This drastically reduces the computation requirement. It may be noted that in scanned images of handwritten text only about 3% pixels or less are black

2.5 Writer identification

AR coefficients computed from an image written by a specific writer characterize that writer. Say, there are *w* writers; each of them contributes one sample. Let $\dot{\theta}_i$ be the estimated AR model coefficients for the *i*-th writer. For an unknown sample, at first the AR model coefficients are computed. Let $\dot{\theta}$ be the estimated coefficients for this sample. Next, the Euclidean distance between this sample and any of the *N* samples of the reference database is computed as follows

$$d(\dot{\theta}, \dot{\theta}_i) = \left\| \dot{\theta} - \dot{\theta}_i \right\|^2 \qquad (7)$$

It is decided that the given sample is written by the *j*-th
writer if

$$d(\hat{\theta},\hat{\theta}_j) > d(\hat{\theta},\hat{\theta}_i) \forall i, i \neq j \; .$$

2.6 Experimental results

Two datasets are used to conduct the experiment. First dataset is known as RIMES [5]. The training set used for writer identification task consists of 382 writers each contributed a letter containing reasonable amount of text. The letters are written in French. The test set used here consists of 100 samples. Test samples contain smaller (one-third or less) amount of text than that of the training samples. Each of the writers contributing these test samples has also given training samples. Therefore, ideally there should not be any rejection while identifying the writer for a given test sample. The second dataset has been developed at the Indian Statistical Institute (ISI), India. ISI developed dataset consists of samples from only 40 native Bengali writers. Each writer has contributed two samples; each containing different text. One sample per writer is used in the training set and another sample forms the test dataset. Both the training and test samples are of comparable size. Samples contain about 200 words or more. Earlier, this dataset was used for handwriting recognition purpose [6].

At first, writer identification performance is tested on RIMES dataset. Gray images are converted into binary ones. Results are shown in Table-1. Effectiveness of using three different contexts as shown in fig. 1 are investigated separately. It is observed that bigger contexts outperform smaller one, e.g. 34-order AR coefficients perform better than 24- order coefficients. Identification results in lower resolution are inferior as reported in Table-1 therefore, further experimental results are only reported on the original image resolution, i.e. 300dpi. Interesting to note that top-1 results are not impressive (at best 57%) but the accuracy rapidly increases to a significant level (at best 97%) when top 10 choices are considered. To compare this performance with an existing technique, we consider the study in [7]. The identification method in [7] uses allograph level features and when tested on RIMES, it achieves an accuracy of 73% when top choice is considered. However, the accuracy is increased to only 84% when top 10 choices are taken into account.

This reveals the potential of the proposed method for writer identification. Unlike an allograph-based technique (e.g. a grapheme-based method [7]), it does not use any knowledge about the script but shows a power of identification that is comparable with that of a technique using allograph-level features

Script independence of the proposed method is verified on ISI Bengali dataset. Table-2 reports identification results on ISI Bengali dataset. Compared to RIMES, identification accuracies are slightly better for ISI dataset. Two important aspects can be attributed for this: dataset consists of only 40 writers and the test samples are of considerable sizes (text contains 200 or more number of words). A test sample containing adequate handwritten data helps in properly estimating the AR coefficients. In case of RIMES samples, training samples contain enough handwritten text but handwritten contents in test samples are quite small. Moreover, number of writers in RIMES is 382.

The capability of the method in handling multi-script environment is tested by mixing the RIMES and ISI samples together. Therefore, number of writers in this mixed dataset becomes 422 (382 French and 40 Bengali writers). Test set contains 140 samples (100 French and 40 Bengali). The identification results are reported in Table-3. Accuracies are 61% and 95% corresponding to the consideration of only the top choice and the top 10 choices. This clearly shows that multi-script handling capability of the method. The identification performance is comparable to the results obtained for a single script.

Next, the results obtained using the three context patterns are integrated through voting method. Table-4 presents the results obtained after combining the results achieved by three different pixel templates. It is noticed that identification accuracies are improved due to this combination. When individual results are integrated, the accuracy is increased by 1% to 2% at different number of top choices

Table-1: Writer identification results on RIMES using different context patterns at different resolutions

Context Type (Refer Fig. 1)	Image Resolution	Recognition Results (% correct) on Rime Dataset # Writers: 382, # Test samples: 100					
		Top 1	Top 2	Top3	Top4	Top 5	Top 10
C_1	300 dpi	55	68	70	70	75	90
	150 dpi	50	59	62	63	64	72
C_2	300 dpi	57	66	75	79	79	92
	150 dpi	47	58	62	64	65	69
C_3	300 dpi	57	62	70	75	77	97
	150 dpi	48	55	57	59	68	73

Table-2: Writer identification results on ISI dataset using different context patterns at original resolution

Context Type (all at 300 dpi)	Recognition Results (% correct) on Bengali Dataset # Writers: 40, # Test samples: 40					
	Top 1	Top 2	Top3	Top4	Top 5	Top 10
C_1	72.5	77.5	82.5	85	85	95
C_2	75	82.5	87.5	87.5	90	97.5
C_3	75	80	82.5	85	87.5	100

Table-3: Writer identification results on RIMES+ISI dataset

Context Type (all at 300 dpi)	Recognition Results (% correct) on Mixed Dataset # Writers: 422, # Test samples: 140					
	Top 1	Top 2	Top3	Top4	Top 5	Top 10
C_1	58.6	70.1	71.4	72.1	75	88.6
C_2	60.7	69.3	76.4	79.3	79.3	90.7
C_3	60.7	65.7	71.4	75.7	77.1	95

Table-4: Writer identification results on RIMES+ISI dataset after classifier combination

Recognition Results (% correct) on Mixed Dataset # Writers: 422, # Test samples: 140					
Top 1	Top 2	Top3	Top4	Top 5	Top 10
62.1	70.7	77.9	80.7	81.4	96.4

Chapter 3

OMNI SCRIPT WRITER IDENTIFICATION

3.1 INTRODUCTION*:* We are concerned with two problems: the estimation of the unknown parameters in SAR model and the choice of an appropriate model from a class of such competing model. Assuming Gaussian-distributed variables, we discuss maximum likelihood (ML) estimation methods. In general, the ML scheme leads to nonlinear optimization problems. To avoid excessive computation, an iterative scheme is given for SAR models, which gives approximate ML estimates in the Gaussian case and reasonably good estimates in some non-Gaussian situations as well.

Typically, an image is represented by two-dimensional scalar data, the gray level variations defined over a rectangular or square lattice. One of the important characteristics of such data is the special nature of the statistical dependence of the gray level at a lattice point on those of its neighbours.

The spatial-interaction models characterize this statistical dependency by representing u(s), the gray level at location s, as a linear combination of the gray levels {y(s + s'), s' E N} and an additive noise, where N is called the neighbour set which does not include (0; 0).

After choosing a finite lattice representation, two problems have to be tackled in fitting an appropriate model, namely, a method of estimating the parameters of the model given the structure of the model, and a criterion to choose between different possible structures.

3.2 Estimation Scheme in SAR Model:

A: Model representation and estimation in infinite lattice SAR Model

Assume that the stationary image {y(s)} obeys the infinite lattice SAR Model in (2.1), with associated neighbour set N.

$$y(s) = \sum_{r \in N} \theta_r y(s+r) + \sqrt{\rho}\,\omega(s). \qquad (2.1)$$

In (2.1), (θr,rεN) and p are unknown parameters, and ω(.) is an independent and identically distributed (i.i.d) noise sequence with zero mean and unit variance. N need not be symmetric. If N is symmetric we assume that the coefficients of the symmetrically opposite neighbors are equal, i.e.,

$$\theta_{k,1} = \theta_{-k,-1}.$$

Note that y(.) is not Markov with respect to any arbitrary bilateral neighbour set N, i.e.,

$$p(y(s) \mid \text{all } y(r), s \neq r) \neq p(y(s) \mid \text{all } y(s+r), r \in N). \qquad (2.3)$$

Given a finite image defined on a square M X M grid ω, we are interested in estimating the parameters of the model characterizing the image. A popular method of estimation is that of least squares (LS), which yields the estimate in (2.4)

$$\hat{\theta} = \left[\sum_s z(s) z^T(s)\right]^{-1} \left(\sum_s z(s) y(s)\right), \qquad (2.4)$$

$$\hat{\rho} = \frac{1}{M^2} \sum_s \left(y(s) - \hat{\theta}^T z(s)\right)^2, \qquad (2.5)$$

$$z(s) - \text{col}\,[y(s+r), r \in N]. \qquad (2.6)$$

One of the drawbacks of the LS is that in general 8 is not consistent for non-unilateral neighbour sets [14].

Another popular method is the ML method, which yields asymptotically consistent and efficient estimates.

B : SAR Model representation on finite lattices

Suppose we partition the finite lattice ω into mutually exclusive and totally inclusive subsets Ω_I, the interior set, and Ω_B, the boundary set, such that,

$$\Omega_B = \{s = (i, j): s \in \Omega \text{ and } (s + r) \notin \Omega \text{ for at least one } r \in N\},$$

and

$$\Omega_I = \Omega - \Omega_B.$$

For every $s \in \Omega_B$, there exists a r ε N so that $(s + r) \notin \Omega$ and consequently y(s + r) is not defined by (2.1). Hence (2.1) needs modifications.

The toroidal lattice SAR model for a finite image $y(s + r)$ is defined by two equations for s in Ω_I, and Ω_B, as in (2.10) and (2.11).

$$y(s) = \sum_{r \in N} \theta_r y(s + r) + \sqrt{\rho}\, \omega(s), \qquad s \in \Omega_I, \tag{2.10}$$

$$y(s) = \sum_{r \in N} \theta_r y_1(s + r) + \sqrt{\rho}\, \omega(s), \qquad s \in \Omega_B, \tag{2.11}$$

$$\begin{aligned} y_1(s + (k, l)) &\text{ with } s = (i, j), \\ &= y(s + (k, l)), \quad \text{if } (s + (k, l)) \in \Omega \\ &= y[(k + i - 1) \bmod M + 1, (l + j - 1) \bmod M + 1], \\ &\qquad \text{if } (s + (k, l)) \notin \Omega. \end{aligned} \tag{2.12}$$

In the RHS of (2.1 l), y_1, takes the role of y in (2.10). y_1,(s) in (2.12) is a function of y(r), $r \in \Omega$,even when $s \notin \Omega$. If the image y(.) were folded into a torus, $y_1(s) = y(s)$.

Equations (2.10) and (2.11) give M^2 equations relating the image variables {y(s)} and i.i.d random variables {ω(s)}. Denoting y and ω as M^2x1 vectors of lexicographic ordered arrays {y(.)} and {ω(.)}, (2.10)-(2.11) can be rewritten as $B(\theta)y = \sqrt{\rho}\omega$

3.3 Least Square and ML Estimates

The LS estimate in (2.4) is not consistent for toroidal lattice SAR model. The ML estimation method yields asymptotically consistent and efficient estimates. To obtain an expression for the log-likelihood function, we impose a Gaussian structure on the noise sequence ω(.). Then the likelihood of the observations can be written as

$$\ln p(y \mid \boldsymbol{\theta}, \rho) = \ln \det B(\boldsymbol{\theta}) - \left(M^2/2\right) \ln 2\pi\rho - \frac{1}{2\rho} \sum_{\Omega} \left(y(s) - \boldsymbol{\theta}^T z(s)\right)^2, \quad (2.14)$$

The ML estimates are obtained by maximizing (2.14) with respect to θ and p. Since the log-likelihood function is non quadratic in θ, the estimation involves the use of numerical optimization methods, such as Newton-Raphson approach, which are computationally expensive.

3.4 Choice of Neighbours in SAR Model

We briefly discuss the need for choosing appropriate SAR model consider possible approaches and suggest decision rules. From one-dimensional time series analysis, it is known that a model of appropriate order should be fitted to obtain good results in applications like forecasting and control. A similar situation is true in the case of two-dimensional models. The problem becomes more difficult due to the rich variety of model structures. In the two-dimensional case, within the same class of SAR models, different neighbour sets account for different patterns .Thus the result varies considerably depending on how similar the underlying model is to the true model, and so the use of appropriate neighbour set is important..

3.5 Bayes Decision Rule For Choice Of the SAR Model

We formulate the problem and give the test statistic. The actual derivation of the test statistic can be done by using standard Bayes decision theory as in [8] for SAR models.

Suppose we have three sets N_1, N_2, and N_3 of neighbours containing m_1, m_2, and m_3 neighbours respectively. Corresponding to each N_i, we have a toroidal SAR model C_i,

$$y(s) = \sum_{r \in N_k} \theta_{kr} y(s+r) + \sqrt{\rho_k}\,\omega(s), \qquad s \in \Omega_I, \tag{4.1}$$

$$y(s) = \sum_{r \in N_k} \theta_{kr} y_1(s+r) + \sqrt{\rho_k}\,\omega(s), \qquad s \in \Omega_B, \tag{4.2}$$

where $y_1()$ is as in Section II-B, $\theta_{k,r} \neq 0$, $r \varepsilon N_k$, and $p_k > 0$, k = 1,2,3 .and the noise sequence $\{\omega(s)\}$ is Gaussian.

The models C,, i = 1,2, . . . are mutually exclusive. According to Bayesian theory, the optimal decision rule for minimizing the average probability of decision error chooses the model C, which maximizes the posterior probability $P(C_l,/y)$, where y is the vector of all the observations. The quantity $P(C_l,/y)$ is computed from the Bayes rule, $P(C_l/y) = p(y/C_l)\,P(C_l)/P(y)$. We will set $P(C_l)$ same for all i in the absence of any contrary information, so that

$$p(y/C_k) = \int p(y/\boldsymbol{\theta}, \rho)\, p(\boldsymbol{\theta}, \rho/C_k)\, |d\boldsymbol{\theta}|\, d\rho.$$

Let the models are $C_1, C_2, C_3 \ldots\ldots C_k$
let $\theta \sim \theta_1, \theta_2, \ldots\ldots\ldots \theta_k$ be the possible values of θ.
Let we know $p(y \mid \tilde{\theta}) = p(y_1, y_2, \ldots. y_n \mid \theta)$, here θ represent $C_1 \ldots\ldots C_k$
$p(\theta=\theta_i) = p_i$
is the priory distribution
posterior distribution

$$p(\theta|y_1, y_2, \ldots\ldots\ldots y_n) = \frac{p(y_1 \ldots. y_n \mid \theta_i)\, p(\theta_i)}{\sum_{j=1}^{k} p(y_1, \ldots., y_n \mid \theta_j)\, p(\theta_j)}$$

in case of any priory knowledge about $p(\theta_i)$,we assume that $p(\theta_i)$ is equal for all i, also the lower term in the above expression can be assumed to be constant or independent of θ because this is nothing but $p(y_1, y_2, \ldots\ldots\ldots y_n)$.
so only the numerator term is of interest of us

but $p(\theta_i|y_1, \ldots.. y_n) = p(\theta_i, y_1, \ldots.. y_n) / p(y_1, \ldots.. y_n)$

now

$$p(\theta_1, |y_1, \ldots.. y_n) = p[\theta=\theta_1 | y_1, \ldots.. y_n]$$
$$p(\theta_2, |y_1, \ldots.. y_n) = p[\theta=\theta_2 | y_1, \ldots.. y_n]$$
$$\ldots\ldots.$$
$$p(\theta_k, |y_1, \ldots.. y_n) = p[\theta=\theta_k | y_1, \ldots.. y_n]$$

choose that $\theta=\theta_i$ for which $p(\theta_i|y_1, y_2, \ldots\ldots\ldots y_n)$ is maximum.

So if $C_1, C_2, C_3 \ldots\ldots C_k$ are the models in our hand then choose model C_k
For which $p(C_k|y)$ is maximum

CHAPTER 4

CONCLUSION AND SCOPE FOR FUTURE WORK

The method proposed here has been purely statistical. Though it doesn’t give us an optimal choice of neighbour among all existing neighbours but it facilitate us that if we have a set neighbours in our hand then among those which one is the best.

As far as future work is concerned though this approach is statistically and mathematically correct in its own right but its very difficult to implement . Even i tried to implement it but got stuck in the mid. so there is possibility of improving it towards implementation context

REFERENCES

[1] R. Plamondon and G. Lorette, “Automatic Signature Verification and Writer Identification— The State of the Art,” Pattern Recognition, vol. 22 (2), pp. 107-131, 1989.

[2] M. Bulacu and L. Schomaker, “Text-Independent Writer Identification and Verification Using Textural and Allographic Features,” in IEEE Trans. Pattern-Anal. Mach. Intell. Vol. 29(4), pp. 701-717, 2007.

[3] K. Deguchi, “Two-dimensional Auto-regressive Model for Analysis and Sythesis of Gray-level textures,” in Proc. Of the 1st Intll. Sym. for Science on Form, General Ed. S.
Ishizaka, Eds. Y. Kato, R. Takaki, and J. Toriwaki, pp. 441-449, Tokyo, Japan, 1986.

[4] ITU-T recommendation T.82, “Information Technology-Coded representation of picture and audio information-Progressive bi-level image compression,” March 1993.

[5] E. Grosicki, M. Carré, J. Brodin, and E. Geoffrois, “RIMES evaluation campaign for handwritten mail processing,”, in Proc. of ICFHR, 2008.

[6] A. Lemaitre, B.B. Chaudhuri, and B. Coüasnon, “Perceptive Vision for Headline Localisation in Bangla Handwritten Text Recognition,” in Proc. of ICDAR, pp. 614-618, 2007.

[7] A. Bensefia, T. Paquet, and L. Heutte, “A Writer
Identification and Verification System,” Pattern Recognition
Letters, vol. 26 (10), pp. 2080-2092, 2005

[8] R. L. Kashyap, R. Chellappa, and N. Ahuja, “Decision rules for the choice of neighbors in random field models of images,” Comput.Graphics Image Proc., vol. 15, pp. 301-3 18, Apr. 198 1.

[9].I. T. Tou, “Pictorial feature extraction and recognition via image modeling,” Comput. Graphics Image Proc., vol. 12, pp. 376-406, Apr. 1980

[10]G. R. Cross and A. K. Jain, “Markov random field texture models,” in Proc. IEEE Comput. Sot. Conf. Pattern Recog. Image Proc.,Dallas, TX, pp. 597-601, Aug. 1981

[11]R. Chellappa and R. L. Kashyap, “Synthetic generation and estimation in random field models of images,” in Proc. IEEE Comput. Sot. Conf. Pattern Recog. Imuge Proc., Dallas, TX, pp. 577-582, Aug. 1981

[12]D. V. Lindley, “The use of prior probability distributions in statistical inference and decisions,” m Proc. Fourth Berkeley Symp. Math. Stntist. Prob., vol. 1, pp. 453-468, 1961